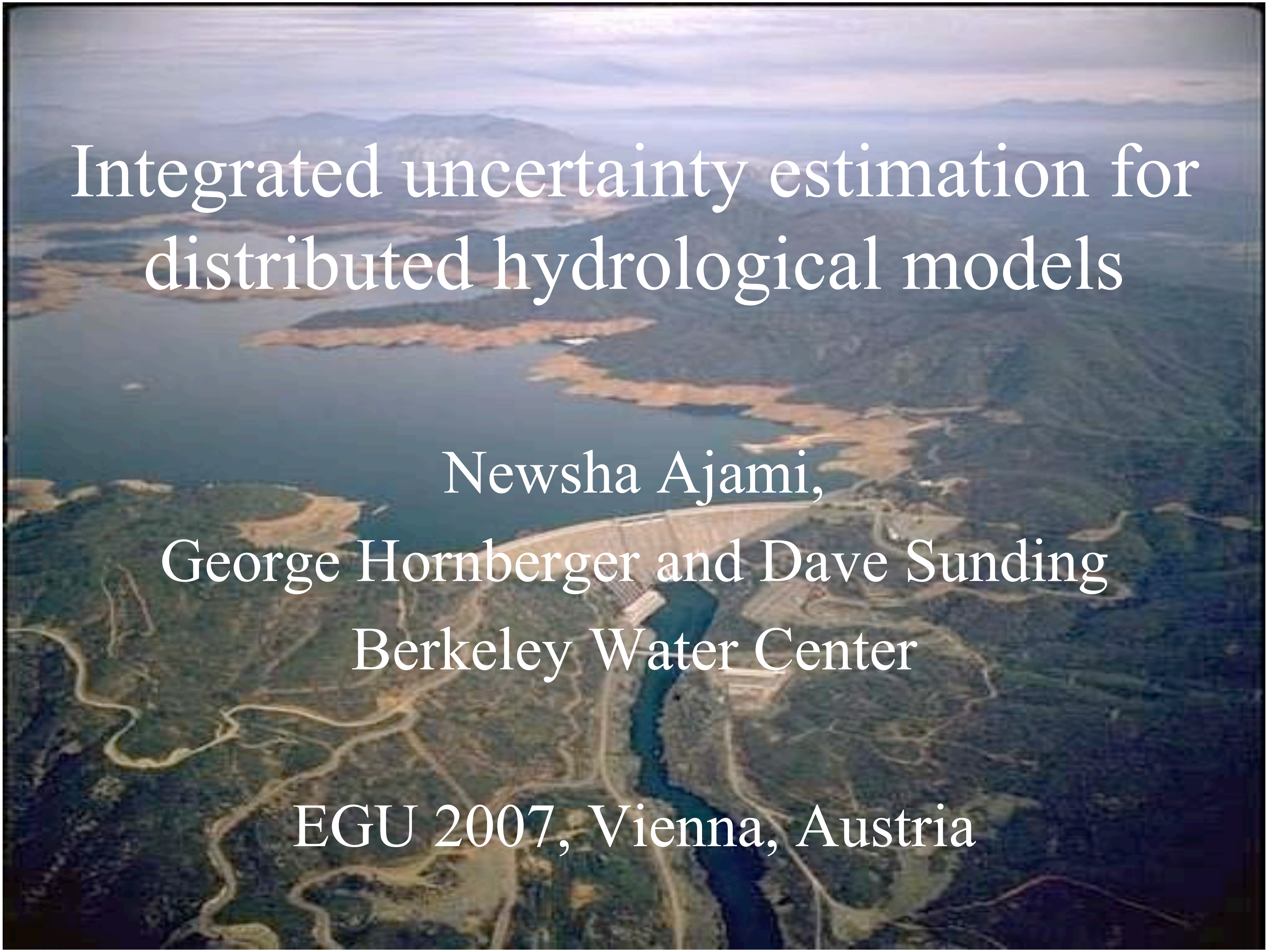
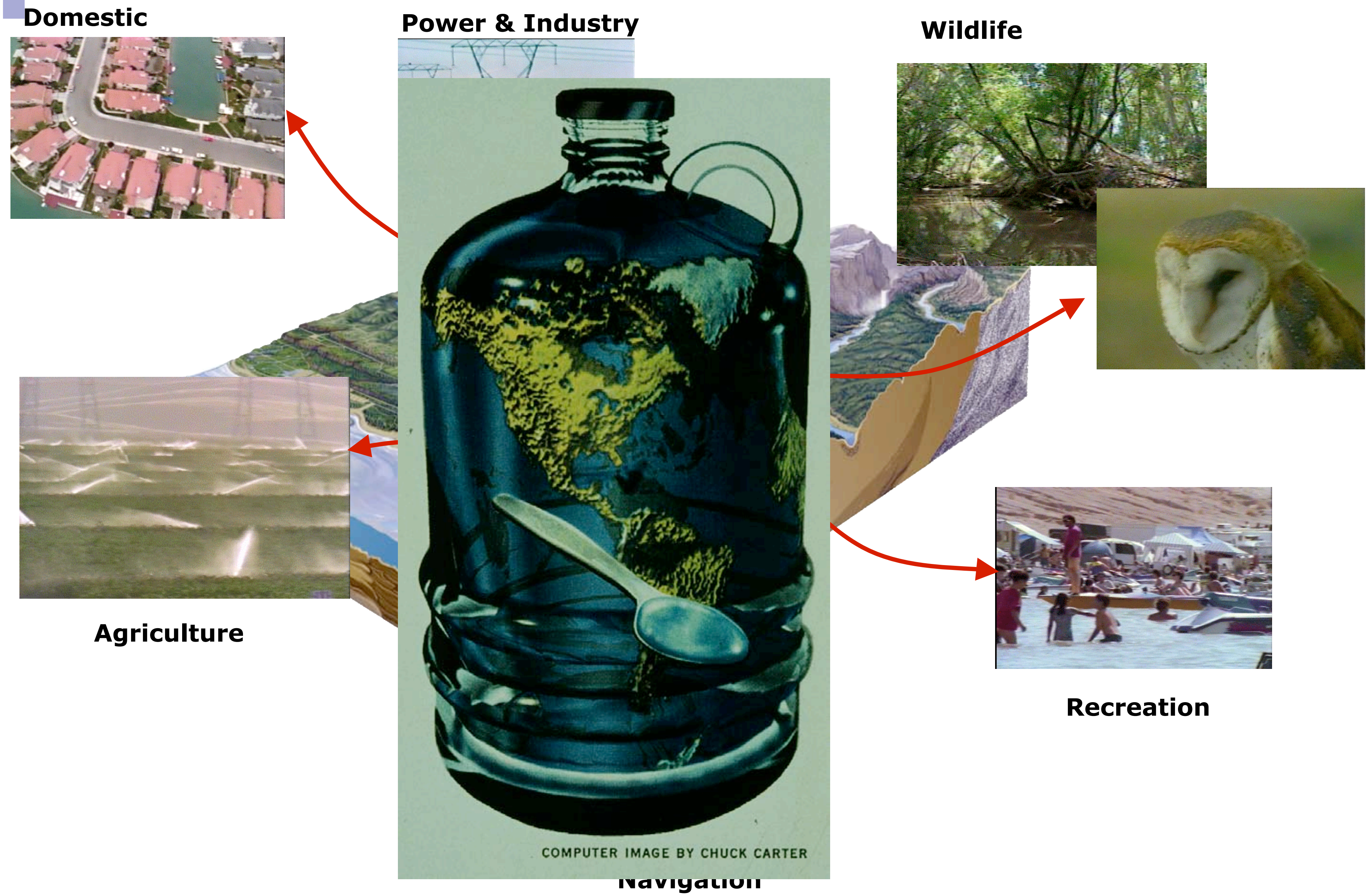


Integrated uncertainty estimation for distributed hydrological models

Newsha Ajami,
George Hornberger and Dave Sunding
Berkeley Water Center

EGU 2007, Vienna, Austria

Competing Demands in California



CAL2030 project: Overview

In the near future California will be dealing with

Population growth

California

Neighboring states (Arizona-Nevada)

Water quality regulations and environmental requirements

Climate Change

Shrinking snow pack

Time shift in water supply

Growing Water Demand

Shrinking Water Resources

California's water crisis

This calls for an integrated, efficient and sustainable plan for managing the water resources which is one of focuses of the Berkeley Water Center

CAL2030 project: system integration

- This integrated system will include an open and flexible platform that connects all California's water systems.
- Why an open platform?
  - More efficient resource management by allowing decision makers to test different possible coordinated operation scenarios.
  - Improved system reliability in term of water supply by considering:
    - uncertainty in future hydrologic events (e.g. impacts of climate change).
    - uncertainty within the management system (e.g. modeling processes).
    - disaster management issues such as exploring alternative water supply sources in case of a catastrophe.

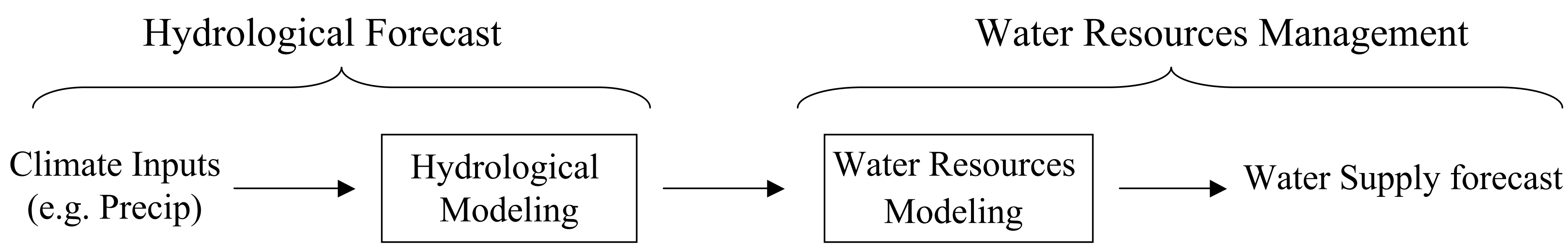
CAL2030 project: pilot project

Conduct a pilot project to focus on some of the raised issues in a smaller scale by:

- Identifying and assessing *end-to-end uncertainty* in a water resources management system with multiple users such as Sacramento River Basin.

- Evaluating if more accurate estimation of the uncertainty leads to sustainable management of our limited water resources in the state of California.

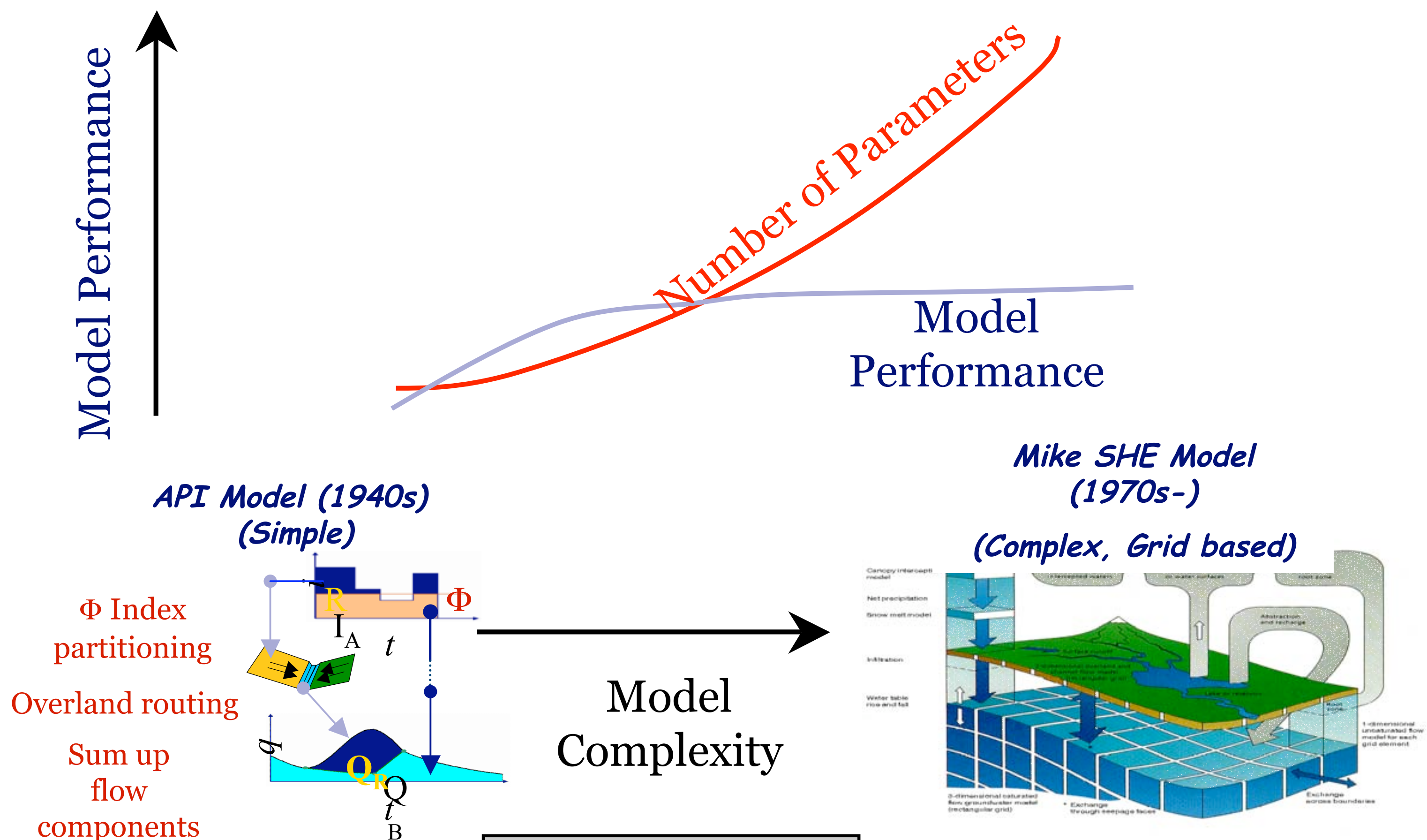
- Two steps:



Accounting for Hydrological Uncertainty

- Models: Three distributed hydrologic models to generate streamflow ensembles.
  - Hydrologic MODel (HYMOD,5 par)
  - Simple Water Balance model (SWB, 5 par)
  - SACramento Soil Moisture Accounting (SAC-SMA) Model (13 par)
- Study area: Upstream of Shasta reservoir in Sacramento basin (including all the 12 catchments that contribute to the inflows to Shasta).
- Hydrologic data: Monthly precipitation and temperature data from 1962-1994 for each sub-catchment.
- Model parameters assumed identical over the whole basin.

Hydrological forecasting: Performance versus Complexity



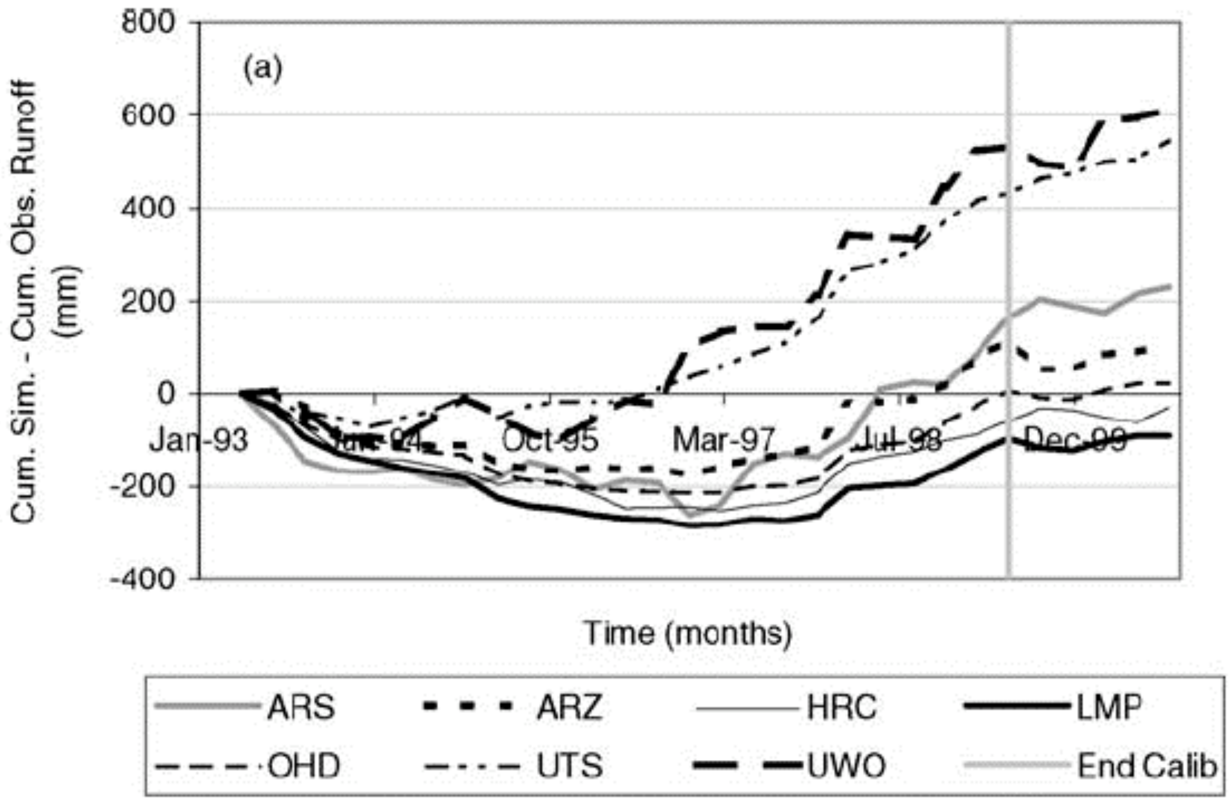
MANY MODELS

Models, no matter how complex,

are simple mathematical representation of the real world.

Performance of Various Distributed Models

Many distributed hydrologic models exist right now which generates ***dissimilar results*** under the same condition using ***the same forcing data***. This was confirmed under the first Distributed Modeling Intercomparison Project (DMIP I).

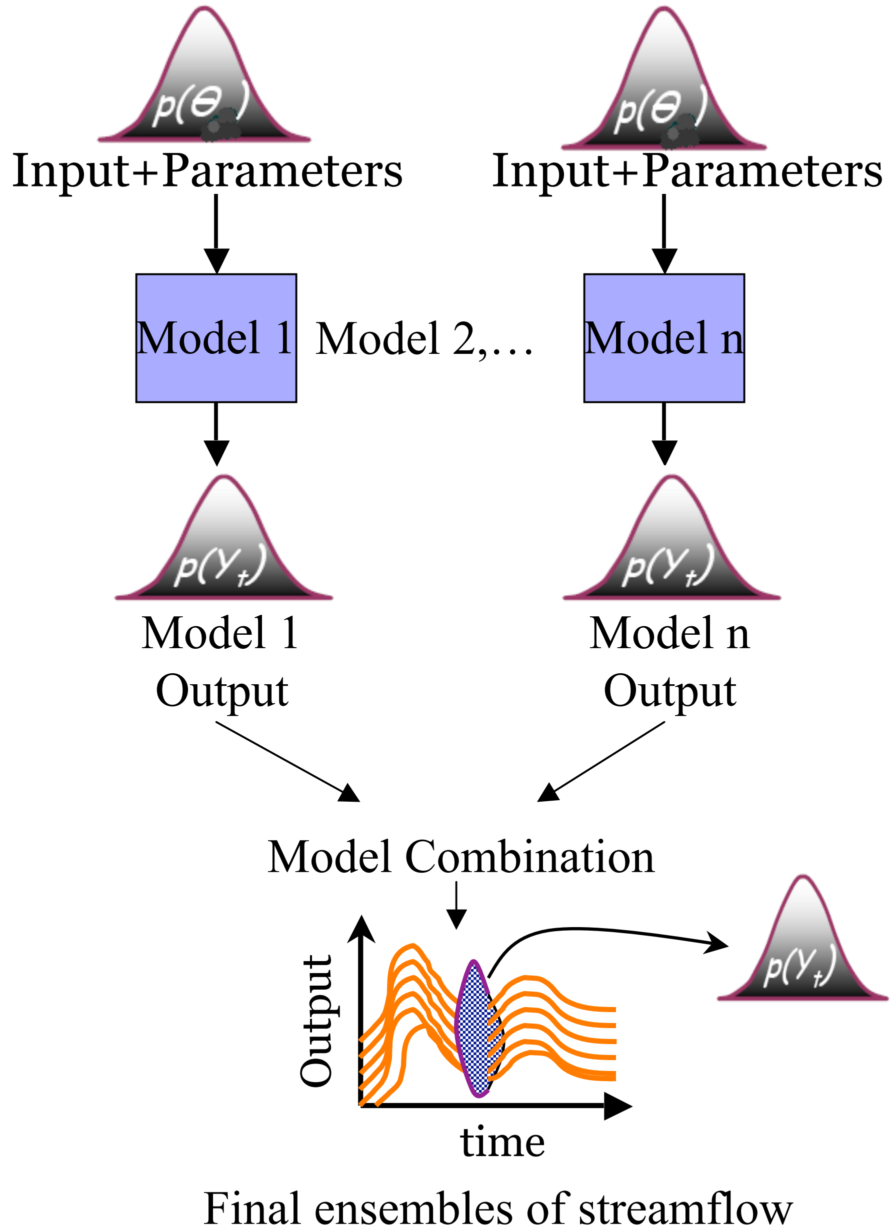


Cumulative simulation errors for calibrated hydrologic models: Illinois River basin at Watts

(DMIP Results, (From Reed et al., 2004))

Accounting for hydrological uncertainty

- Integrated Bayesian Uncertainty Estimator (IBUNE; Ajami et al., WRR, 2007).
- Framework that accounts for uncertainty in input forcings, model parameters and model structure.
- Optimization + MCMC + Model combination



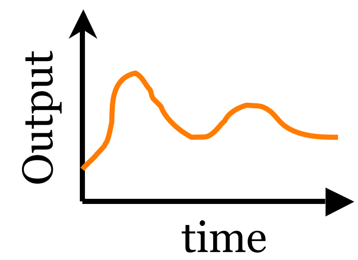
Accounting for Input and Parameters Uncertainty

We can formulate the problem here as follows for model M_k:

Model k

Streamflow estimate
From model k at time t ← $y_{k,t}=f(I_t, \theta, M_k, t)$

Input at time t **Model parameters**

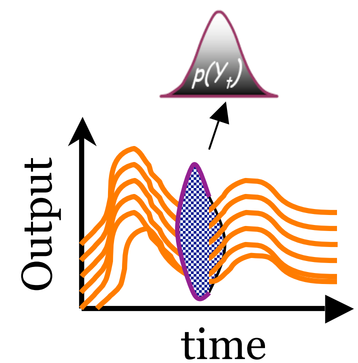


So,

what do we want? → probability of the estimated streamflow

based on the available data:

D= [observed input (I), Observed Streamflow (y_{obs})]



$$p_k(y_t|\theta,D, M_k) \propto p_k\,(\theta|D, M_k)$$

How to account for input uncertainty

Introduce a Input Error Model → multiplier (ϕ_t) drawn at each time step from the same distribution with unknown mean m_ϕ, and standard deviation σ_ϕ,

$$I_t = \phi_t \cdot I_t^{obs}, \ \phi_t \sim N(m_\phi, \sigma_\phi)$$

$$\theta_I = [m_\phi, \sigma_\phi] \rightarrow$$

Model parameters

in $p_k(\theta|D, M_k)$, θ Includes $[\theta_I, \theta_M]$

Input error model parameters

D= [observed input (I), Observed Streamflow (y_{obs})]

- We want to estimate the probabilistic quantity θ, given *D and M*, i.e., $p(\theta|D,M)$.
- Markov Chain Monte Carlo (MCMC) method is ideal for solving above problem
- We used the Shuffled Complex Evolution Metropolis (SCEM-UA) method for this study (See Vrugt et al., WRR, 2003).

Bayesian Model Averaging- BMA

- Madigan et al. (1996) --->

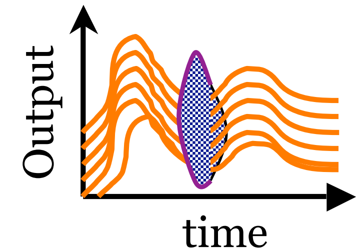
$w_k = p(Mk|D)$

Likelihood of model *Mk* being a true model -- > Weights should sum up to unity

$$\sum_{k=1}^{K} w_k = 1$$

$$p(y \mid M_1, M_2, M_3, D) = \sum_{k=1}^{3} p(M_k \mid D) \cdot p_k(y \mid \theta, D, M_k)$$

D= [observed input (I), Observed Streamflow (yobs)]



Estimated in the first step

•EM (Expectation-Maximization) method for estimating the weights for this study.

Consensus Prediction and Uncertainty associated with it:

- The consensus prediction (predictive mean) and the associated uncertainty of y are:

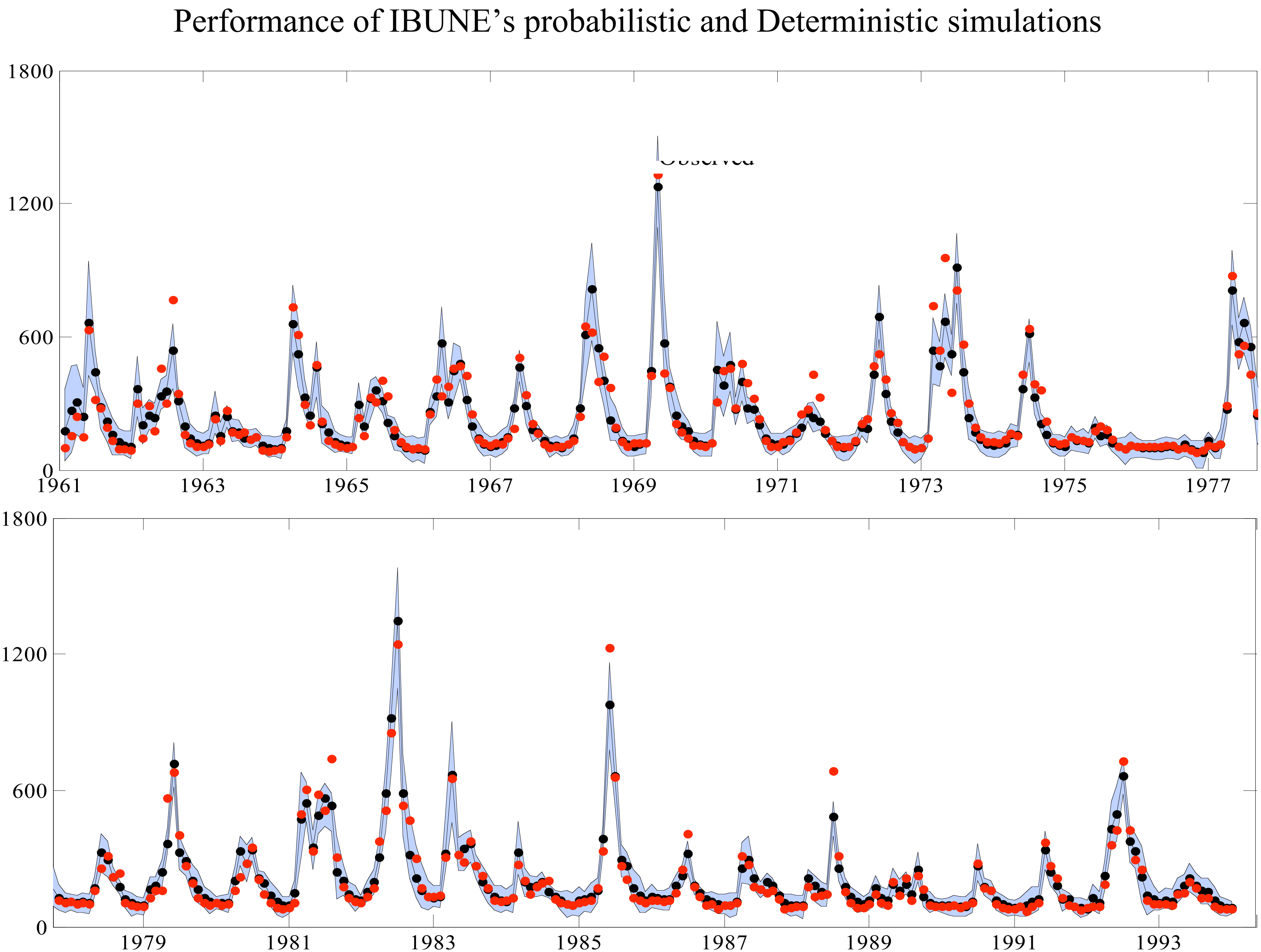
$$E(\mathrm{y}|D) = \Sigma\, w_k \bullet E(\mathrm{y}|M_k, D)$$

- posterior variance of y decomposes into

$$Var[y \mid M_1, M_2, M_3, D] = \sum_{k=1}^{3} w_k \left(M_k - \sum_{i=1}^{K} w_i M_i \right)^2 + \sigma^2$$

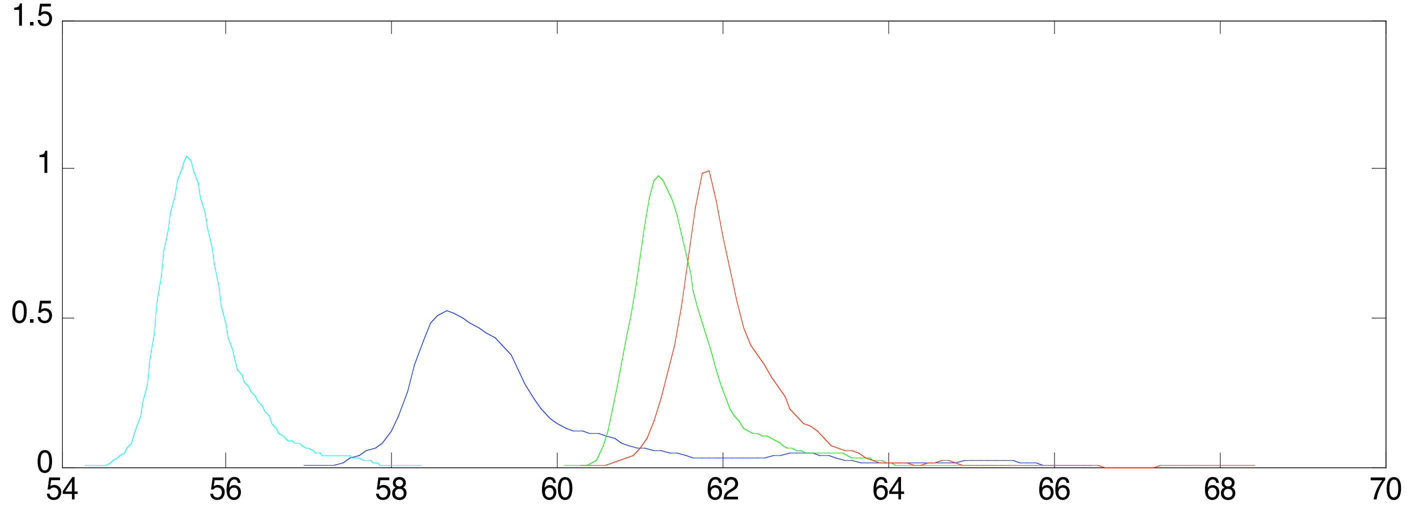
= Between-Forecast variance + Within-Forecast Variance

normally not accounted (i.e. assumed zero) ---- > not true, unless the best forecast were always exact

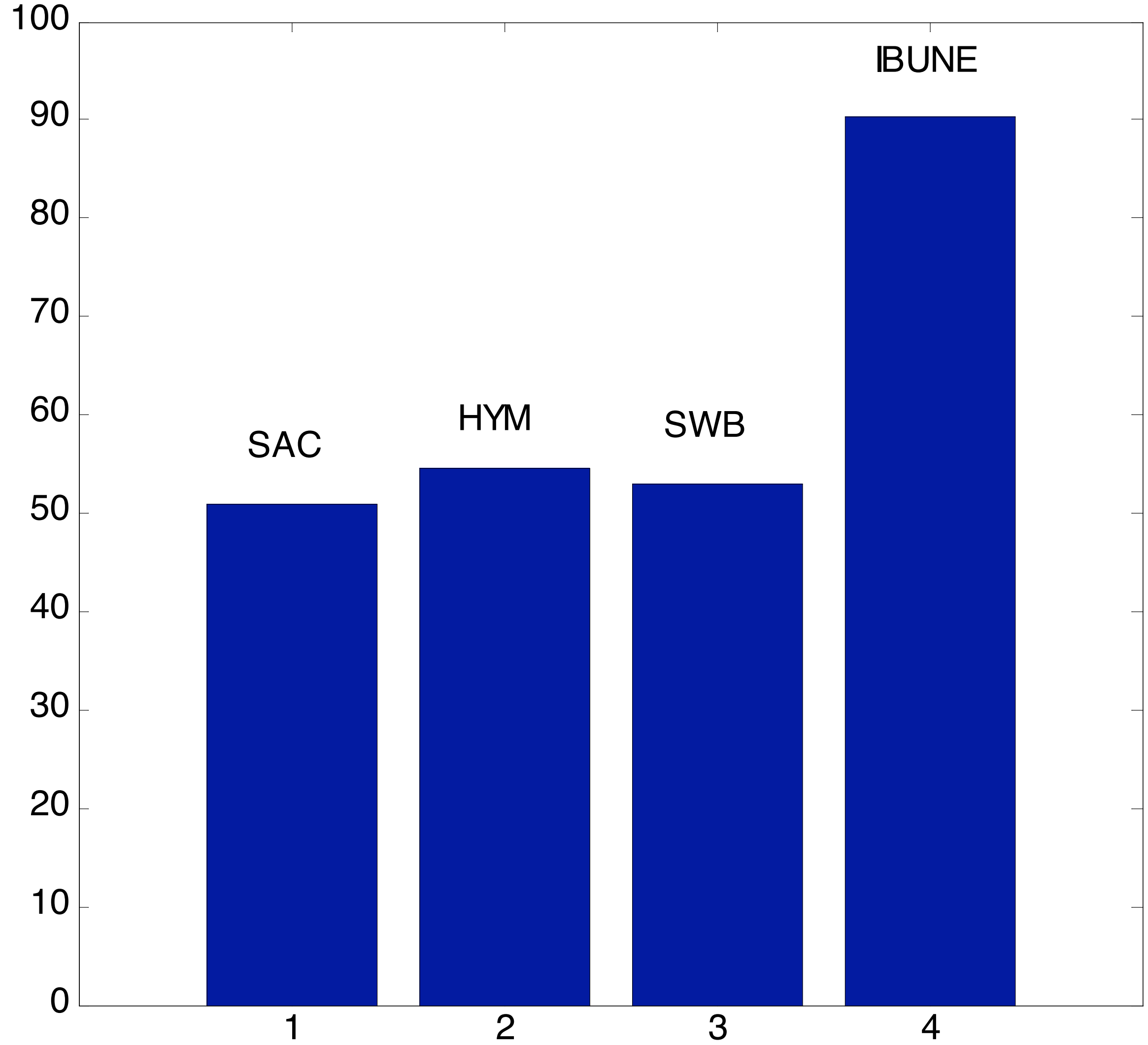


Performance of IBUNE's probabilistic and Deterministic simulations
Observed
1800
1200
600
0
1961
1963
1965
1967
1969
1971
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993

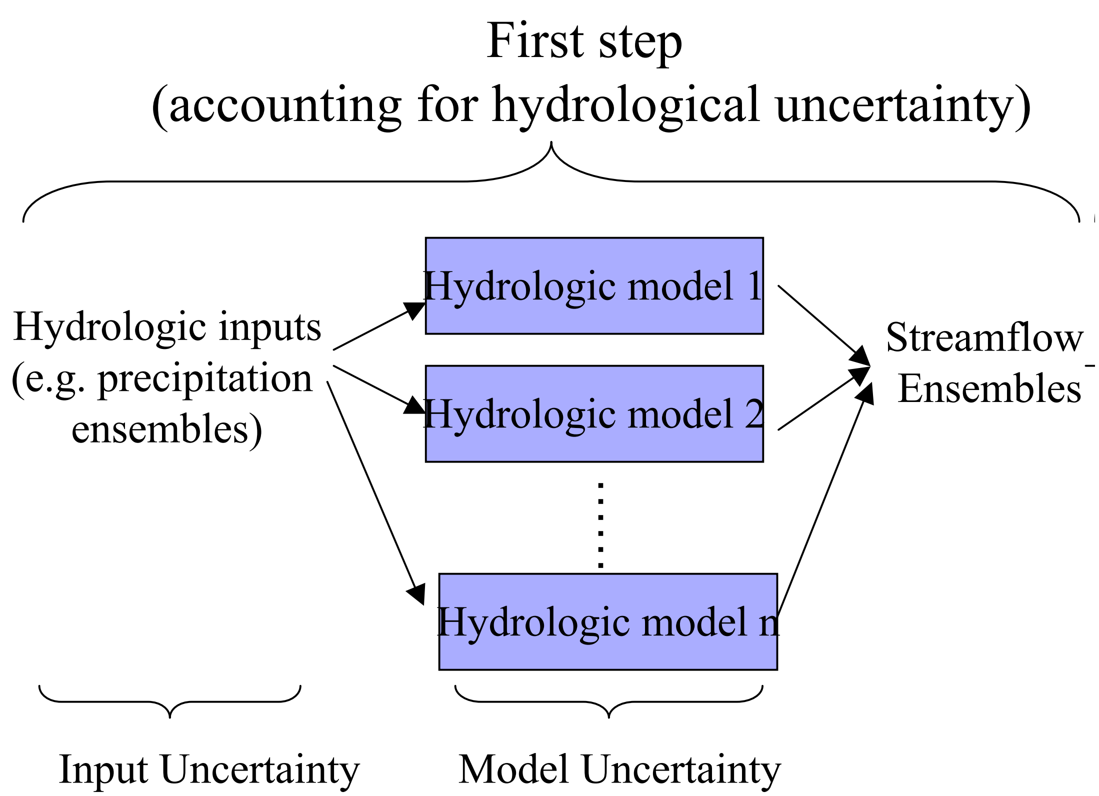
IBUNE versus individual models



IBUNE versus individual models

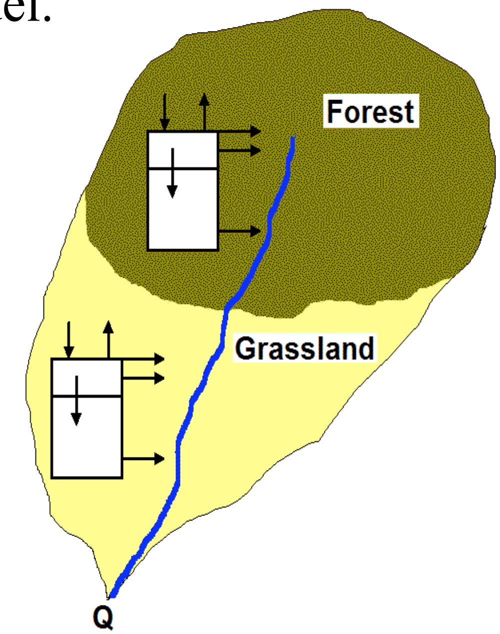


Water Resources Management under Uncertainty

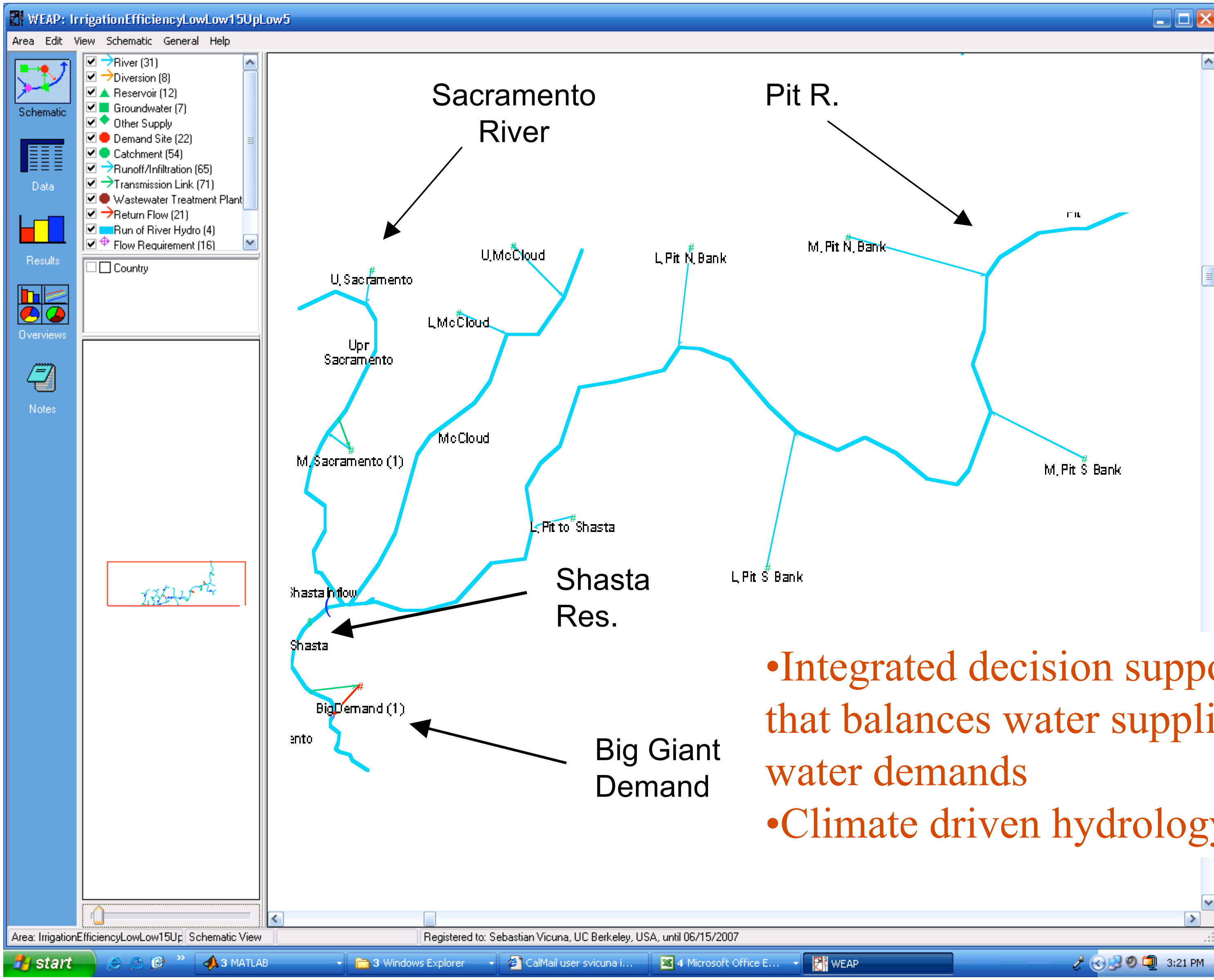


Propagation of hydrological uncertainty

- Propagate the estimated uncertainty through a water management and planning model such as WEAP.
- WEAP includes hydrologic module and management module.
- Hydrologic module: simple 5 parameter hydrologic model.
- Distributed based on the land class within every sub-catchment. Five different land classes therefore 25 parameters were calibrated.
- Looking at the inflow to Shasta Dam.
- Single aggregated demand which represents the water demand south of Shasta.
- Evaluating the reliability of water supplies by analyzing the estimated uncertainty.

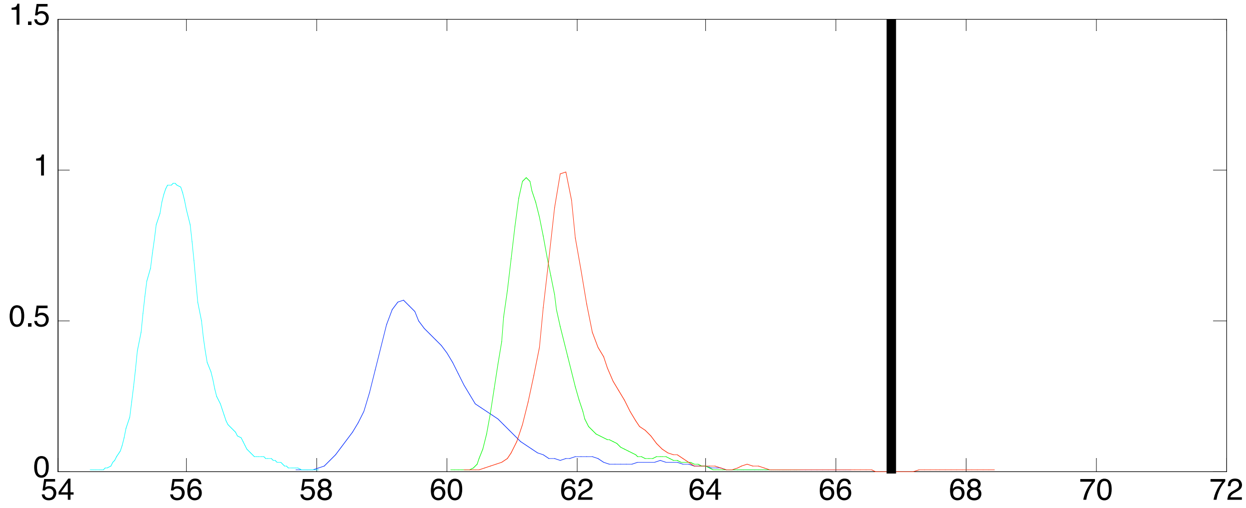


WEAP model

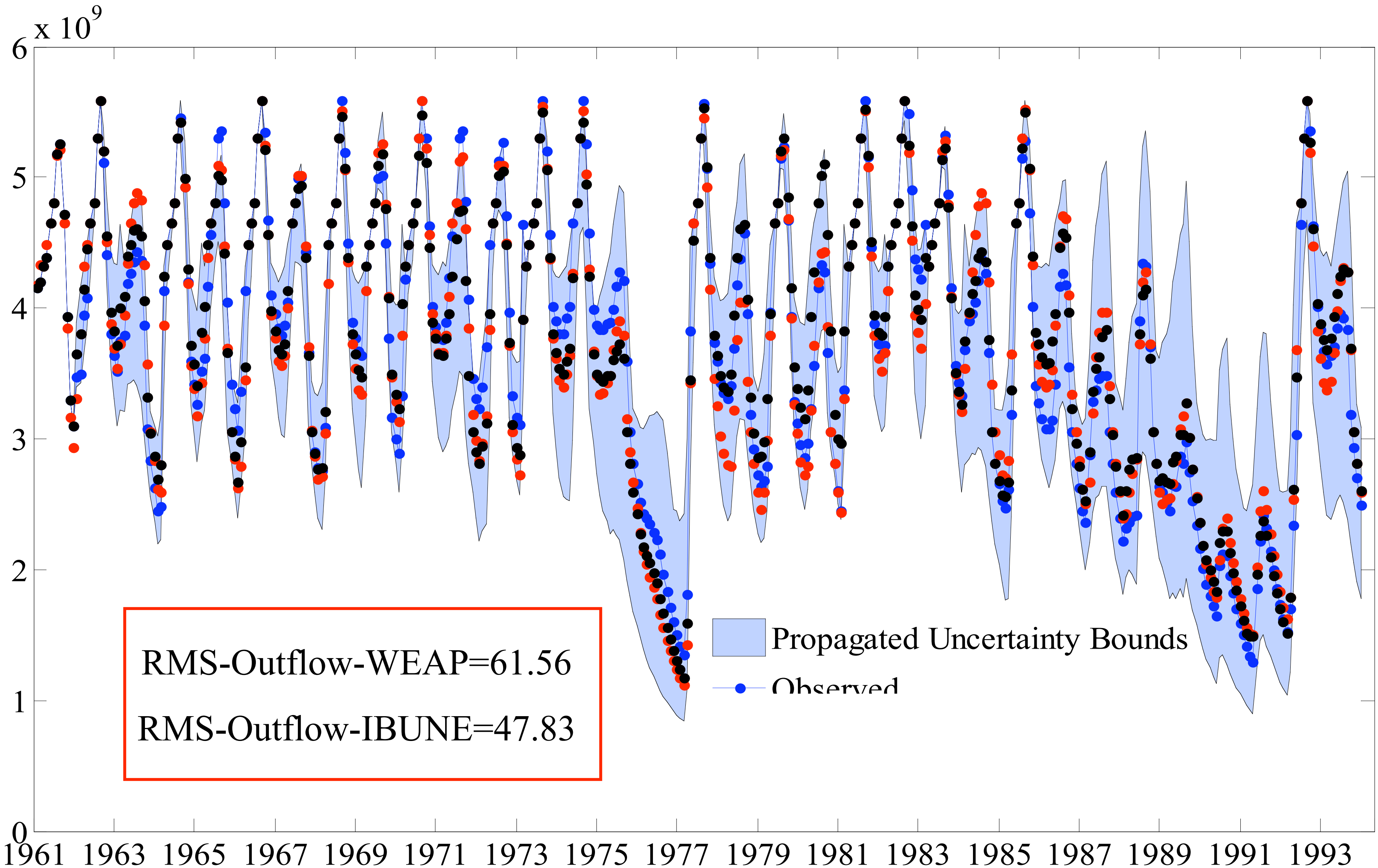


- Integrated decision support system model that balances water supplies and multiple water demands
- Climate driven hydrology

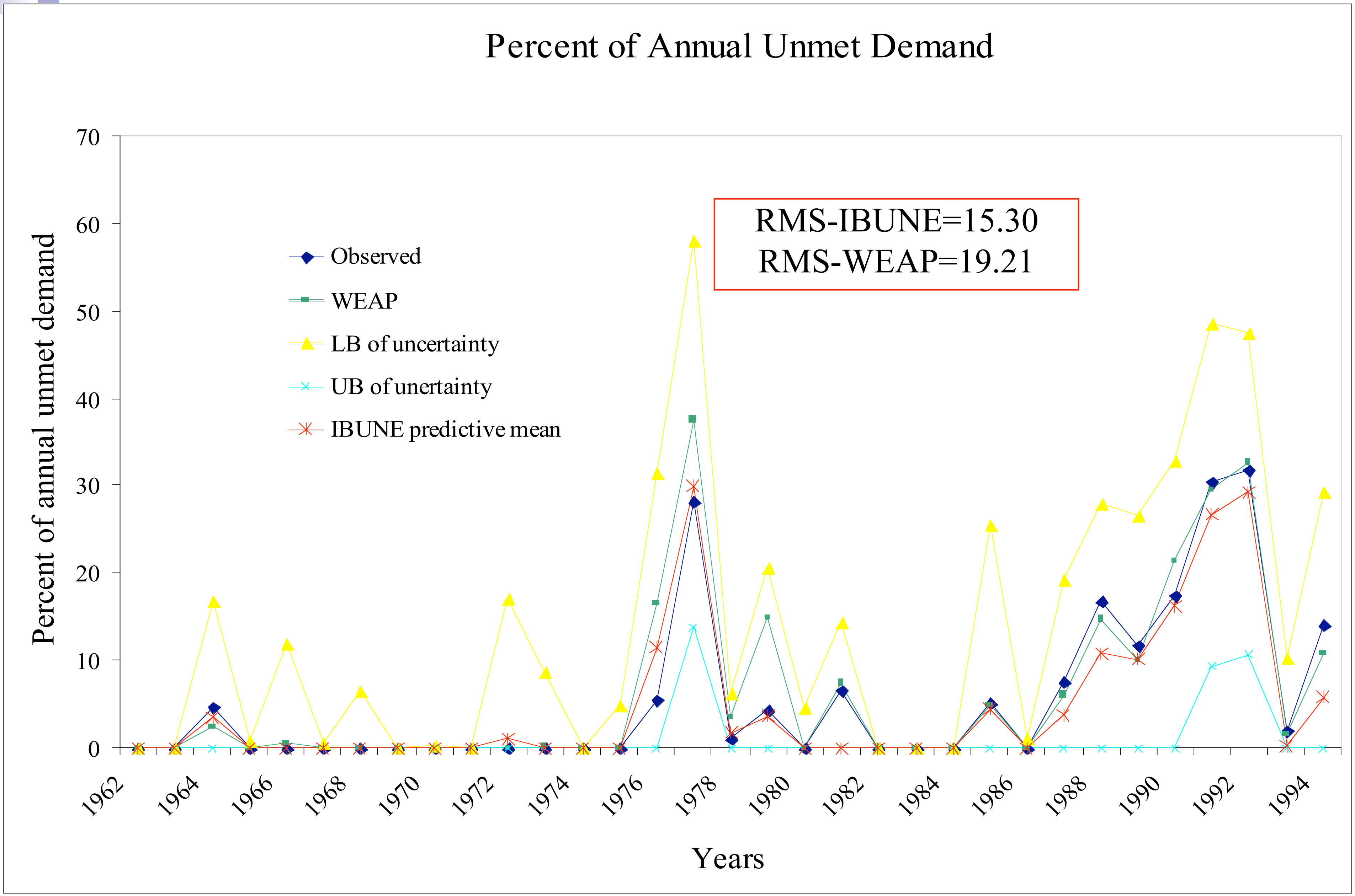
WEAP versus IBUNE



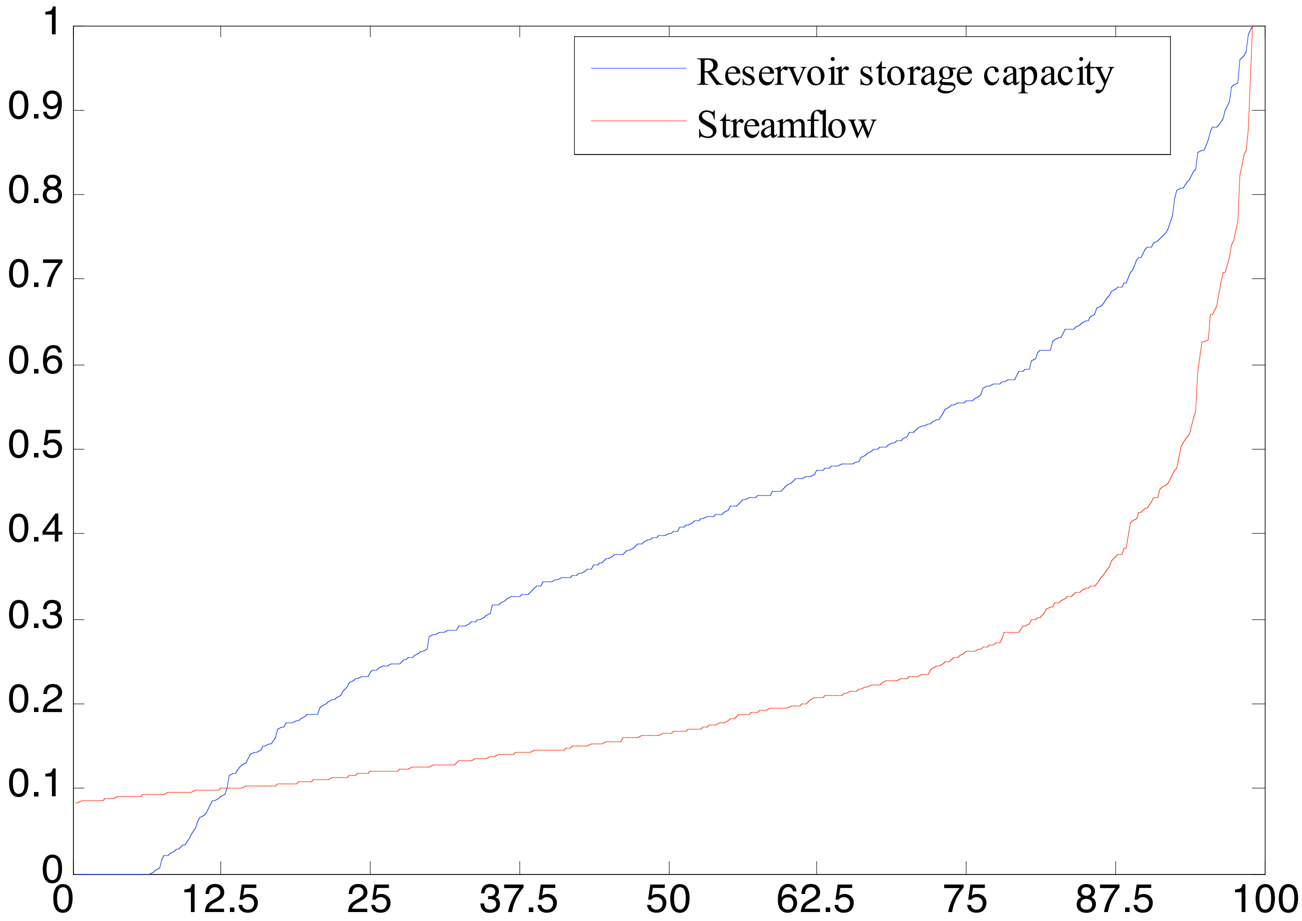
Reservoir Storage Volume



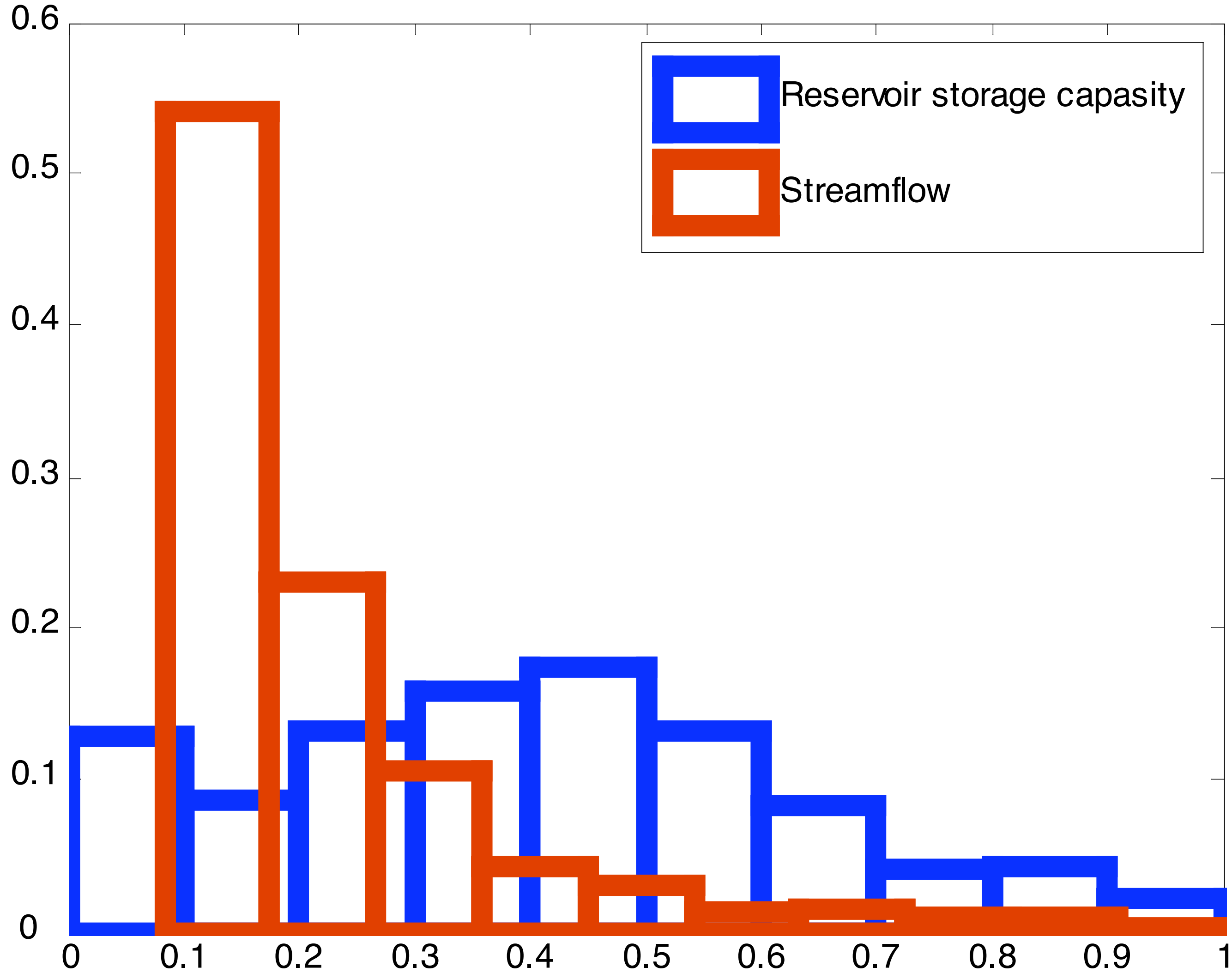
Percent of Annual Unmet Demand



Normalized width of 95% uncertainty bound



Distribution of width of 95% uncertainty bound



Conclusion

- IBUNE is an innovative step towards more accurate and reliable hydrological forecasts, including floods and water supply.
- Accounting for input uncertainty and model structural uncertainty (considering multiple models) considerably improves prediction of water management variables.
- As the temporal resolution decreases, the spatial resolution loses its importance.
- Accuracy of our reservoir outflow predictions was improved almost by 23%. Such improvement can lead to more efficient operation of reservoir consequently more efficient management of water resources.
- The characteristic of hydrologic uncertainty changes as it is propagated through a water resources management tool such as WEAP.

Thanks

Questions?

Man is a complex being; he makes the deserts bloom and lakes die. (Gil Stern)

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